
Multi-Modality Integration

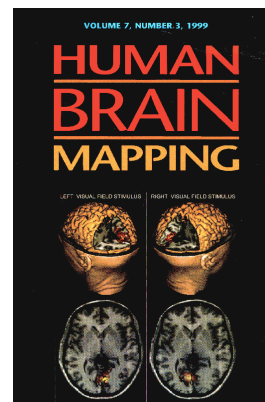
David Schmidt, John George, Doug Ranken, and
C. C. Wood

Biophysics Group, Los Alamos National Laboratory
Los Alamos, New Mexico, USA



Background (review)

Spatial Bayesian Inference analysis
published in Human Brain
Mapping, vol 7, p. 195, 1999.



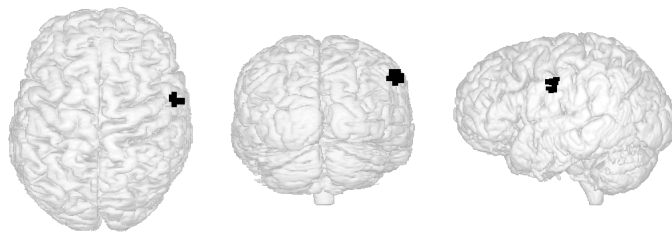
Bayesian inference

- Formal use of prior information.
- Results in a posterior probability distribution.
- Use Markov Chain Monte Carlo to numerically generate samples from the posterior distribution.
- All inferences are drawn from the (numerically sampled) posterior probability distribution.



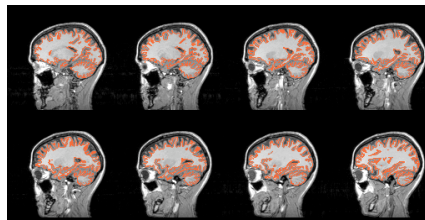
Example with simulated data

- Active region used to generate simulate data.

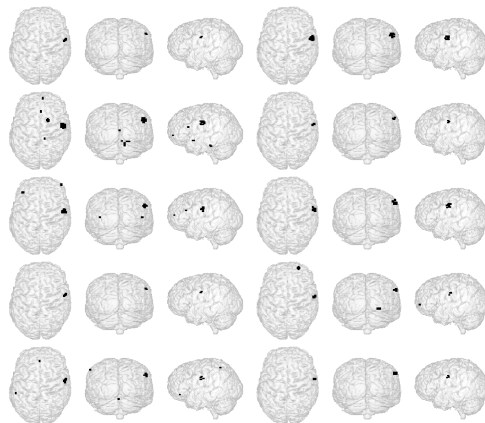


Prior information

- Anatomical location and orientation information from MRI.
- Neural activity limited to a variable number of variable size active regions, defined by tagged cortical voxels within a bounding sphere.

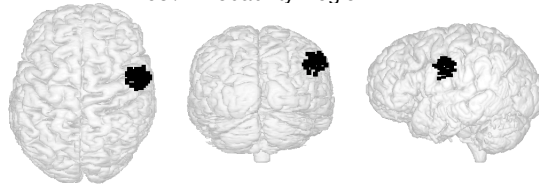


Results from Spatial Analysis

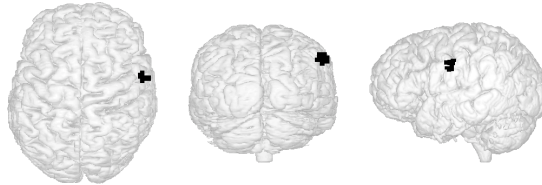


Results from Spatial Analysis

95% Probability Region

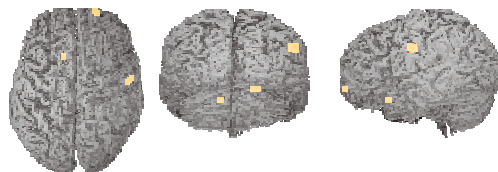


True Active Region

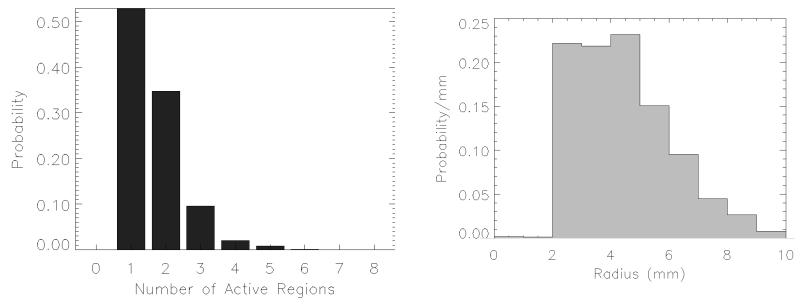


Results from Spatial Analysis (continued)

Most Likely Result



Results from Spatial Analysis (continued)

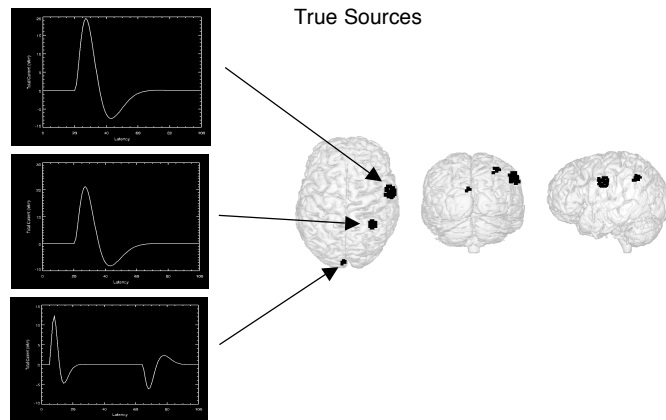


Extension to temporal domain

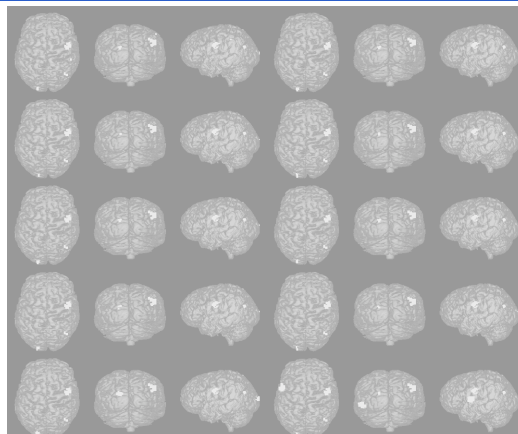
- Sources have a temporal extent.
- Temporal correlation as prior information.
- Increase in information results in more rugged posterior distribution.



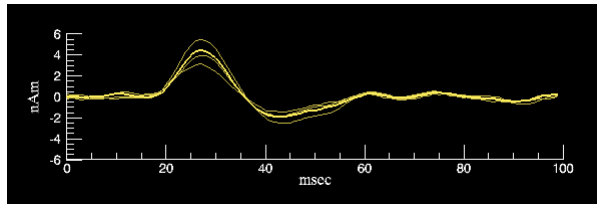
Example from Simulated Data



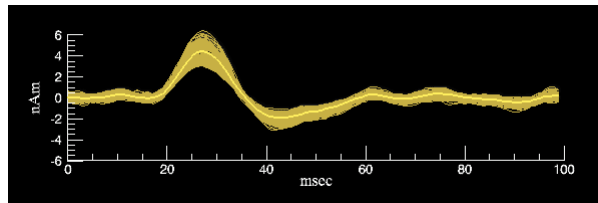
Sample Active Regions



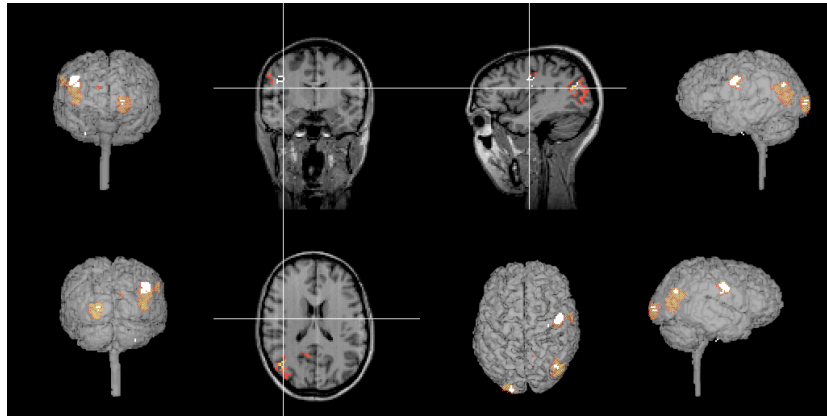
Sample Time-Courses for Anterior Region



Distribution of Time-Courses



Results in spatial and anatomical domains

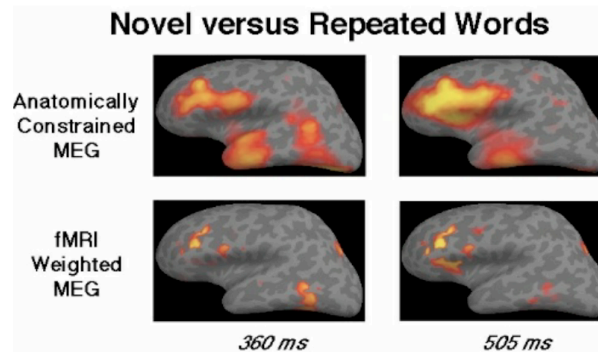


Integration with fMRI



Other integration strategies

- MGH: fMRI weighted MEG linear inverse.



Multi-Scale Modeling

David Schmidt (P-21) Balu Nadiga (CCS-2) David Sharp (T-13)

- In non-linear systems, small scale dynamics affect large scale behavior.
- Computer simulations of a system over a large domain (e.g. ocean) require a very large grid to resolve small scale phenomenon (e.g. eddies).
- Often a coarser grid, that does not resolve the small scale phenomenon, is used in order for the simulation to run in a reasonable period of time.
- The differential equations to be simulated are then modified to try to mimic the effects of the unresolved sub-grid phenomenon.



Closure

- Original equation to be integrated

$$\partial q / \partial t = F(q)$$

- Effect of fields on a grid

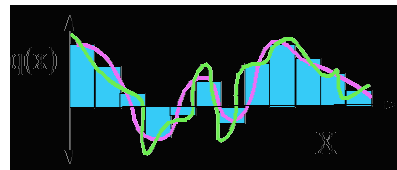
$$\partial \bar{q} / \partial t \neq F(\bar{q})$$

- Modify equations such that

$$\tilde{F}(\bar{q}) \sim \overline{F(q)}$$



Stochastic closure

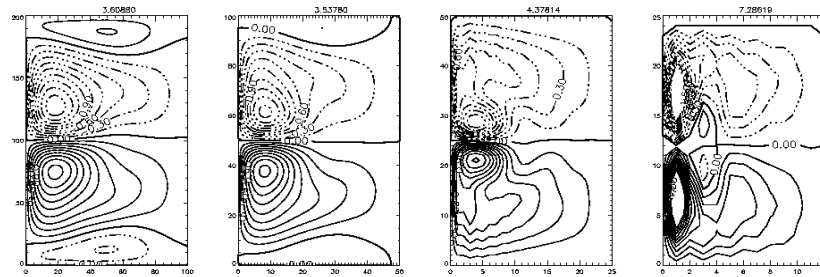


- There are many different continuous fields ($q(x)$) that could have produced a given field on a grid (blue bar graph).
- There should be a distribution of closure relations $P[\tilde{F}(\bar{q})]$ from which elements are drawn at random as the system is being simulated over time.
- This distribution may be found by simulating the system on a fine grid, that resolves the small scale phenomenon, but on a small domain.



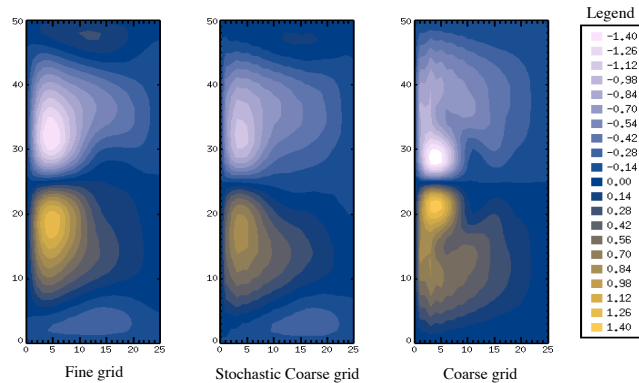
Example: simple basin model with uniform wind forcing

- Effects of grid size on time-averaged stream function.



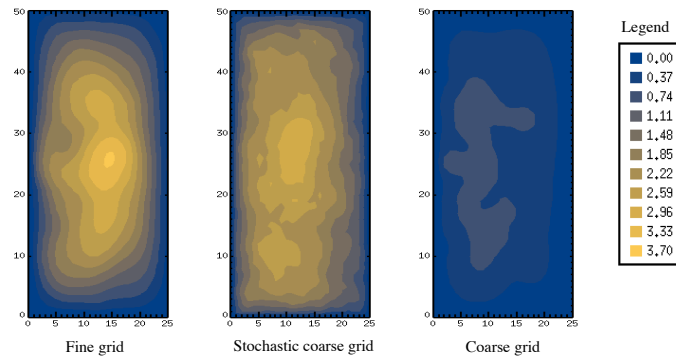
Results from stochastic closure run

- Average stream function



Results from stochastic closure run

□ Temporal variability (standard deviation) of stream function



Stochastic closure summary

- Small-scale phenomenon are treated stochastically.
- Exact temporal ordering is lost but time-averaged quantities (even multiple moments) are retained.
- Well-suited for uncertainty quantification.

